UNMANNED AERIAL VEHICLE DYNAMIC MODEL IDENTIFICATION USING MIXED ESTIMATION BEFORE AND AFTER MODELING METHOD

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Abstract—The unmanned aerial vehicle dynamic model is identified with the use of combination of two different methods called Estimation before Modeling and Estimation after Modeling, using Kalman filter and available measurements. Tuning of filter is one of the difficult stages of the estimation using Kalman filter. It can be made easier to tune Kalman filter by using the Estimation before Modeling method because in this method estimation and modeling of aerodynamic forces and moments are done in two stages. In the Estimation before Modeling method at the first-stage aerodynamic forces and moments are estimated without a priori structure and in the second stage estimated forces and moments are modeled versus suitable state variables. Dimension of augmented state vector for Kalman filter is reduced by using the Estimation before Modeling method. Combination of the Estimation before Modeling and Estimation after Modeling methods are suggested to achieve observability and simplicity of filter tuning. Linear accelerometers out of the center of gravity purposely are used to measure the linear and angular accelerations to achieve better observability. Bounds of uncertainties for estimated aerodynamic coefficients are calculated using diagonal elements of covariance matrix. Suggested method can be used to identify any flight vehicle dynamics and find accurate mathematical models for flight simulators.

Index Terms—Unmanned aerial vehicle; Kalman filter; estimation; aerodynamic coefficient; estimation before modeling and estimation after modeling.

I. INTRODUCTION

Due to the high nonlinearities, time varying and uncertainties of the mini unmanned aerial vehicle (UAV) dynamics, a lot of classical and advanced control methods have been used to design and synthesize the control system in the autopilot systems to guarantee a smooth desirable trajectory navigation. Attractive features of the robust controllers are that on-line computation kept to a minimum and their inherent robustness to additive bounded disturbances. It must be considered that robust controllers require a priori known bounds on the uncertainty. Then it is necessary to model nonlinear equations of motions and literalized at suitable operating points and trim conditions for the purposes of robust control design. The goal of uncertainty modeling is to improve robust performance while maintaining the validity of the model.

Various techniques of system identification find a nominal model and its uncertainty bound. First important question is what are the effects of the particular choice of nominal model and the structure in which the uncertainty described when dealing with robust control analysis and synthesis?

The choice of nominal model affects the method used for the control system design. According to the nominal model of system, goals and problems of control, existing limitations, and technical means of implementation may affect its certain properties. Thus, in the adaptive use of reference models, the order of the system and nominal model must be the same for convergence of adaptation algorithms. For robust control methods applications, it is important that control system keeps the stability and performance properties in the presence of internal and external disturbances of the system. In this case, the rule of the nominal model synthesis should be selected for maximum robustness of control system with the widest deviations from the nominal parameters of the object. Thus, in the synthesis of the nominal model as the procedure of simplification or reduction of the original model, it is necessary to use a suitable criterion function. If the synthesis of the nominal model aims to simplify or reduce model order, the following known methods to obtain simplified or nominal models: a comparison principle, method of singular perturbation, method of weighting functions, method of matrix inequalities and the method of approximation or reduction. For example, for systems with limited resources to control, nominal model must be chosen with the energy criterion.

Second section of the present paper deals with the identification of flight systems dynamics using Estimation before Modeling (EBM) and Estimation after Modeling (EAM) combined method. And the third section, discusses the simulation results of the case study in this paper. Finally, conclusions and suggestion for further research and study were presented.
II. FLIGHT SYSTEM IDENTIFICATION WITH THE MIXED EBM-EAM METHOD

It is possible to say that the aerodynamic model of flight vehicles is the most difficult part in the identification of flight vehicle dynamic system. Therefore, identification of flight vehicle dynamic system converted to the identification of the aerodynamic model. The aerodynamic coefficients estimation of flight vehicles from flight-test data, as post flight analysis has been an active topic since last three decades, [1] – [4].

There are four important principles known as Quad-M that must be considered in the identification of flight vehicle: good Maneuvers or persistent excitation, sufficient Measurements, selection suitable Model, and Method, [1], [2], [4]. In general, estimation of aerodynamic coefficients can be done in two ways:

1) Estimation before Modeling: in this method for aerodynamic forces and moments are not considered structure priori. They are totally estimated at first and then they are modeled versus suitable state variables. That is the problem of estimation at the first stage is converted to the model or unknown inputs estimation. For the aerodynamic forces and moments at the first stage stochastic Gauss-Markov models are used, [2], [4], [5].

2) Estimation after Modeling: in this method for the aerodynamic forces and moments a priori structures are considered and after that process of parameters estimation of these structures are conducted. Then these aerodynamic parameters augmented to state vector and estimated with them.

Different approach to the EAM methods can be listed as follows [1] – [3], [5]:

1) Equation error method.
2) Output error method.
3) Filter error method (mixed state and parameter estimation).

To estimate the aerodynamic forces and moments acting on a flying object using EBM method, the following methods can be used [2], [3]:

1) Singular systems theory.
2) Stochastic models for aerodynamic forces and moments.
3) Use a combination of Kalman filter and neural networks.
4) Combination of stochastic models and an optimization method.

There are many aerodynamic coefficients that must be estimated in the identification of flight vehicle dynamics. Therefore, the size of augmented state vector becomes very large, if the EAM method is used. So it becomes difficult to achieve a good observability and simplicity using only EAM method. On the other hand, there are some aerodynamic coefficients that are not estimated well by using only the EBM method and this bad estimations affect the other aerodynamic coefficients estimations. Here it is introduced a combined method that uses the EBM and EAM methods with each other.

The proposed mixed EBM-EAM method for identification of the UAV dynamics is presented in Fig. 1. In the first step aerodynamic forces and moments, along with the state variables are estimated by the extended Kalman filter. In the second step, estimates of forces and moments are modeled as functions of estimated state variables. Neural networks can be used for aerodynamic model fitting in the second step, [5].

In the next section for a given UAV, aerodynamic coefficients for longitudinal channel are identified by using the introduced combined method.

III. ESTIMATION OF THE LONGITUDINAL MODEL OF THE UAV

It is possible to separate the linearized equations into longitudinal equations and lateral-directional equations for flight vehicle. This is possible because the two sets of perturbation motions are uncoupled for a symmetric aircraft in steady cruise, climbing or descending flight. For steady flight, in the longitudinal channel assumed that $\dot{V}, \dot{q}, \dot{\theta},$ and $\dot{\alpha}$ derivatives of air velocity, pitch angular acceleration and rate and angle of attack rate, respectively are zero. The longitudinal state, control, and disturbance vectors are:

$$\Delta X_{Lon} = \begin{bmatrix} \Delta u & \Delta w & \Delta q & \Delta \theta & \Delta x & \Delta z \end{bmatrix}^T,$$

$$\Delta U_{Lon} = \Delta \delta_E, \Delta W_{Lon} = \begin{bmatrix} \Delta u_w \\ \Delta w_w \end{bmatrix}.$$  \hspace{1cm} (1)

The linearized longitudinal equations of motion take the general form:

$$\Delta X_{Lon} = A_{Lon} \Delta X + B_{Lon} \Delta U + E_{Lon} \Delta W.$$  \hspace{1cm} (2)

In this linear model, it is necessary to estimate these aerodynamic coefficients:

$$X_u, X_w, X_q, Z_u, Z_w, Z_q, M_u, M_w, M_q, X_\delta, Z_\delta, M_\delta.$$  \hspace{1cm} (3)

Using the following five available measurements and their standard deviations:
\[
\begin{align*}
    y_{1n} &= \nu_{\text{GPS}} + \nu_1, \\
    y_{2n} &= w_{\text{GPS}} + \nu_2, \\
    y_{3n} &= q + \nu_3, \\
    y_{4n} &= a_x + \nu_4, \\
    y_{5n} &= a_z + \nu_5,
\end{align*}
\]
\[
\begin{align*}
    \sigma(\nu_1) &= 0.5 \left[ \frac{\text{m}}{\text{s}} \right], \\
    \sigma(\nu_2) &= 0.5 \left[ \frac{\text{m}}{\text{s}} \right], \\
    \sigma(\nu_3) &= 0.5 \left[ \frac{\text{deg}}{\text{s}} \right], \\
    \sigma(\nu_4) &= 0.1 \left[ \frac{\text{m}}{\text{s}^2} \right], \\
    \sigma(\nu_5) &= 0.1 \left[ \frac{\text{m}}{\text{s}^2} \right].
\end{align*}
\] (4)

First Stage:
Estimation of the aerodynamic forces and moments time histories along with the state variables

Second Stage:
Modeling of the estimated aerodynamic forces and moments as functions of the estimated state variables

Fig. 1. The proposed two stage mixed EBM-EAM method for the UAV dynamic model estimation

We used linear accelerometers out of the center of gravity purposely to measure the linear and angular accelerations to achieve better observability. It is assumed that the control system inputs sufficiently dominate the motion in comparison with the effects of the turbulence and other unknown disturbances. In addition, all the measurements are without biases. Here the aerodynamic coefficients, forces and moment are appended to the state vector to create a bilinear system with these augmented states:

\[
X_{\text{aug}} = \begin{bmatrix} 
\Delta u & \Delta w & \Delta q & X & Z & M_1 & M_{\delta}\n\end{bmatrix}^T,
\] (5)

where \( X = X_u\Delta u + X_w\Delta w + X_q\Delta q + X_{\delta}\Delta \delta \),

\[
Z = Z_u\Delta u + Z_w\Delta w + Z_q\Delta q + Z_{\delta}\Delta \delta ,
\]

\[
M = M_u\Delta u + M_w\Delta w + M_q\Delta q + M_{\delta}\Delta \delta = M_1 + M_{\delta}\Delta \delta ,
\]

and \( w_0 \) and \( u_0 \) are nominal linear velocities in body frame, \( X, Z, M \) are aerodynamic forces and moment, \( M_1 \) is the part of the aerodynamic moment, \( M_{\delta} \) is elevator aerodynamic moment coefficient. We used stochastic Gauss–Markov models for them in augmented Kalman filters; it is clear that we estimated aerodynamic forces and part of aerodynamic moment with the EBM method and \( M_{\delta} \) with the EAM method. In the second stage all other aerodynamic coefficients calculated using the least square method. The estimated aerodynamic forces, moment and coefficient, \( X, Z, M_1 \) and \( M_{\delta} \) for all aerodynamic coefficients are shown in Fig. 2. We can conclude that, good-quality reconstruction of the signals can be obtained using the combined method. It is very important to find correctly bounds of uncertainties for the purposes of robust control system design to prevent instability and overdesign. Comparing estimation error of each state with the bounds created with positive and negative square roots of diagonal elements of the covariance matrix of Kalman filter shows filter performance, [6]. That means estimation errors must be located in \( \pm 3\sigma \). These \( \pm 3\sigma \) bounds are considered as the bounds of uncertainties for estimated aerodynamic coefficients. For example the bound of uncertainties for elevator aerodynamic moment coefficient, \( M_{\delta} \) is \( \pm 17\% \).
IV. CONCLUSIONS

This paper aimed to find the nominal longitudinal model of the UAV by using the EBM-EAM combined method. It shown that it is possible to make easier to tune Kalman filter by using this method. Bounds of uncertainties for aerodynamic coefficients were calculated diagonal elements of the covariance matrix. We used linear accelerometer out of the center of gravity purposely to achieve better observability. This verified software package in simulation environment will be used for processing real flight data, identifying flight vehicle dynamics with introduced EBM-EAM combined method in the future works. In the second stage, Neural Networks can be used for aerodynamic model fitting as functions of state variables.

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П. М. Фархаді. Ідентифікація динамічної моделі безпілотного літального апарату з використанням змішаного методу оцінювання до і після моделювання

Динамічна модель безпілотного літального апарату ідентифікується з використанням комбінації двох різних методів оцінювання: до моделювання та оцінювання після моделювання з використанням фільтра Калмана і доступних вимірів. Налаштування фільтра є одним із складних етапів оцінювання з використанням фільтра Калмана. Можна простити налаштування фільтра Калмана з використанням методу оцінювання до моделювання, оскільки в цьому методі оцінювання і моделювання аеродинамічних сил і моментів здійснюються в два етапи. У методі оцінювання до моделювання на першій стадії аеродинамічні сили і моменти оцінюються без априорної структури, а на другому етапі моделюються сили і моменти як функції від змінних станів. Розмір вектора стану для розширеної моделі Калмана зменшується з використанням методу оцінювання до моделювання. Запропоновано комбінацію методу оцінювання до і після моделювання для забезпечення спостережливості і простоти налаштування фільтра. Лінійні акселерометри, які розміщуються далеко від центру ваги, намічені використовуватися для вимірювання лінійного і кутового прискорень для досягнення кращої спостережливості. Оцінювання невизначеності для оцінених аеродинамічних коефіцієнтів обчислюються з використанням діагональних елементів коваріаційної матриці. Запропонований метод можна використовувати для ідентифікації динаміки літальних апаратів і знаходження точних математичних моделей для симуляторів польоту.

Ключові слова: безпілотний літальний апарат; фільтр Калмана; оцінювання; аеродинамічний коефіцієнт; оцінювання до моделювання та оцінювання після моделювання.

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